ST-Segment Analysis Using Hidden Markov Model Beat Segmentation: Application to Ischemia Detection

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Abstract

In this work, we propose an ECG analysis system to ischemia detection. This system is based on an original markovian approach for online beat detection and segmentation, providing a precise localization of all beat waves and particularly of the PQ and ST segments. Our approach addresses a large panel of topics never studied before in others HMM related works: multi-channel beat detection and segmentation, waveform models and unsupervised patient adaptation. Thanks to the use of some heuristic rules defined by cardiologists, our system performs a reliable ischemic episode detection, showing to be a helpful tool to ambulatory ECG analysis. The performance was evaluated on the two-channel European ST-T database, following its ST episode definitions. The experimentation was performed over 48 files extracted from 90. Our best average statistic results are 83% sensitivity and 85% positive predictivity. Performance compares favorably to others reported in the literature.

1. Introduction

Ambulatory ECG monitoring (AECG) provides accurate and clinically meaningful information about myocardial ischemia (MI) in patients with coronary disease [1]. MI early detection allows fast diagnosis and treatment. Most studies have demonstrated that ST-segment changes are indicative of MI during AECG monitoring. However, it is well known that particular ST deviations can occur for other reasons than MI [1].

Many efforts have been dedicated to the development of computer programs for MI detection: geometric method [2], Karhunen-Loève transform [3], fuzzy-logic [4], neural networks [5], RMS difference series [6]. The first task is to construct the ST deviation function, namely the ST amplitude measured against the baseline of each beat, usually the PQ segment. Nevertheless, algorithm inaccuracies concerning parameter measurement are seen as a source of noise and considered as problematic. That is why some systems, in order to avoid imprecision, impose a fixed offset from the QRS fiducial point to detect the ST segment and employ a filter to attenuate baseline wander.

In this work, we use an original markovian approach for online beat detection and segmentation, providing a precise localization of all beat waves and particularly of the PQ and ST segment [7,8]. Hidden Markov models (HMM) replace the heuristic rules commonly used for detecting the QRS complex, and the beat waveforms. Our beat segmentation approach addresses a large panel of topics never studied before in other HMM related works [9,10]: multi-channel beat detection and segmentation, waveform models and unsupervised patient adaptation. Furthermore, this approach takes advantage of the Mexican Hat wavelet transform during a parameter extraction stage. Wavelets are well localized both in time and frequency domain been suitable for transient analysis and its subband decomposition emphasizes the waves to the detriment of the noise.

Finally, ischemia detection is carried out by a rule based system for two-channel ST-segment analysis which handles the information given by the markovian approach.

2. Methods

The AECG data used in our experimentations are part of the European ST-T database [11]. The evaluation set consists of 48 two-channel ECG recordings of two hours long and sampled at 250 Hz. Each record contains annotations of the ST and T episodes made manually by different cardiologists, but only ST episodes were taken into consideration. The episodes annotations of both channels were merged, giving a total of 120 episodes.

The proposed ischemia detection system is composed of two parts (Figure 1): online beat detection and segmentation; and ischemic episode detection. The first part relies on an original beat detection and segmentation approach using hidden Markov models (HMM). It must be pointed out that ECG segmentation was performed here in a patient-independent context without supervising training. More details on our model is also given in [7,8].

The second part concerns the ischemic episode detector, which is composed of the following stages: ST amplitude deviation, beat rejection, filtering, and ischemia episode detection.

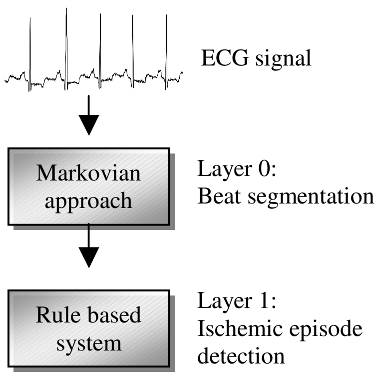

Figure 1. Block diagram of the proposed system for ECG analysis and ischemic episode detection.

2.1. Layer 0: Beat segmentation

Our model considers the heartbeat as a sequence of elementary waves and segments, which respects some heart electrical activity constraints. Each wave and segment is modeled by a specific left-right HMM. Like in a state machine, the electrical constraints are modeled by transitions among models.

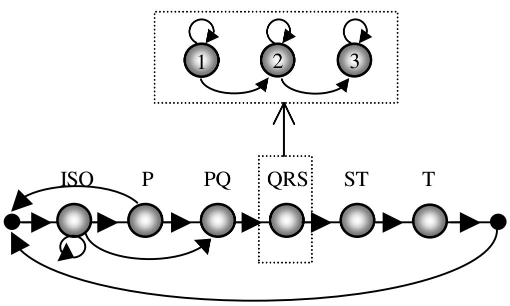

Figure 2. Beat model representing all possible transitions among waveform models. Each waveform model (ISO, P, PQ, QRS, ST and T) corresponds to a specific left-right HMM

Figure 2 presents our proposed beat model. It can be observed that some particular anomalies like a beat without sinus activity (P-wave) and non-conducted P-waves (P-waves not followed by a QRS complex) are considered in the model.

An HMM requires a feature extraction stage for the construction of the observation sequence **O**. We have found Mexican Hat wavelet transform as most appropriate, since it is suitable to peak detection. Moreover, working on different frequency bands improves noise robustness. From our previous work, three wavelet scales were chosen [7].

Each waveform model was trained on a set of wave patterns extracted from the *QT* database using the Baum-Welch method [8]. We constructed multiple models for each wave, since it improves modeling of complex patterns [8]: four 3-states HMM were trained for QRS complex waveforms, two 2-states HMM for the PQ and ST segment, two 3-states HMM for the P wave, two 6-states HMM for the T wave and one 3-states HMM for the isoelectric line (ISO).

The beat segmentation procedure consists of matching the HMM models to the ECG waveform patterns. This is typically performed by the Viterbi decoding algorithm. In our case, the Viterbi algorithm has a double task: to search the most likely HMM corresponding to each waveform pattern and to follow the beat model structure (see Figure 2). Furthermore, it must allow waveform detection information in real-time. The one-pass algorithm was adopted since it fulfills all these requirements [8].

Our HMM model has been conceived to be generic and to work for any ECG signal without the need of a supervised training strategy. In addition, we have implemented a non-supervised training in order to keep tracking of new shapes and adapt accordingly the HMM to them during real time analysis in an ambulatory ECG. Thus, during ECG segmentation, the waveforms attributed to a same model are grouped together. When at least 30 observation vectors per Gaussian pdf are available in one group, then the waveform model is reestimated. We found 30 observation vectors per Gaussian pdf sufficient to carry out HMM training.

Finally, our beat segmentation approach works in one ECG channel (lead) at a time. However, the complementary information of all channels of each record of the database has been explored in order to improve performance. For segmentation purpose, we used a Boolean AND logic. Thus, a beat detection is confirmed every time a QRS complex is detected in both channels. This criterion improves noise robustness and reduces false beat detection.

2.2. Layer 1: Ischemic episode detection

The ST-segment amplitude is measured each time a beat is detected and it always refers to the beat baseline. In our case, the beat baseline is given by the PQ-segment level. Both PQ and ST segment amplitudes are provided by the online beat segmentation stage. According to the ST-T database definitions [11], ST segment amplitude is obtained from a reference point situated 80 ms after the J point (QRS complex end). In the case of sinus tachycardia (heart rate > 120 bmp), ST deviation is measured 60 ms after the J point. The mean value of 5 samples around the reference point was finally retained as ST deviation.

After analysis of a complete AECG record, we obtain two-channel time trends, which are not ready for analysis due to noise and artifacts. Some noise criteria leading to beat rejection and filtering are then applied:

a. *Beat rejection*: abnormal beats and its neighbors are discarded when the difference between the mean baseline level and their baseline value is larger than 0.6 mV. Moreover, we also rejected the neighbor beats.
b. *Filtering*: impulsive noise is attenuated and the ST-segment amplitude is evenly distributed in time. Two simple filtering strategies are employed: median filter of length 3 samples and linear interpolation to resample the trends to 1 Hz [2,6]. An exponential average with a time constant of 20 s. was further applied to smooth the trends [6].

Previously, the ST amplitudes were considered for each channel separately. On the other hand, the episode detection stage exploits combined ST amplitude information. Clearly, two-channels emphasize those episodes showing deviations in both channels [2].

The ST-deviation function depends on the ST amplitude and the reference level of each channel. A simple Euclidian distance is then applied:

$$st[t] = \sqrt{(st_1[t] - ref_1)^2 + (st_2[t] - ref_2)^2} \tag{1}$$

where $st[t]$ is the ST-deviation function, $st_1[t]$ and $st_2[t]$ are the smoothed ST-amplitude, and ref_1 and ref_2 the reference levels of channels 1 and 2 respectively.

However, combining two-channel information is not always possible, since some beats have been rejected in the previous stage. That is why some improvements can be obtained when we switch to single-channels analysis every time beats are missing in one channel. In this particular case, the ST-deviation function becomes

$$st[t] = \left| st_i[t] - ref_i \right| \tag{2}$$

where i is the available channel.

The reference levels are calculated over the first 180 beats. Nonetheless, an adaptive reference level is required because of slow drifts in the ST-deviation function caused by nonischemic factors [2, 3, 6]. Thus, an exponential average filter of 20 minutes time constant is used to adjust continuously the reference level values. The adaptation is stopped any time the ST-deviation function reaches 0.05 mV.

The ischemic episodes are then detected using a decision threshold. We have followed the ischemic episode definitions proposed by the European ST-T Database project [11]. It is coherent with the cardiologist approach, which also used these definitions during ST-change annotations: an ischemic episode corresponds to minimum episode duration of 30 s.; and minimum ST-segment deviation of 0.1 mV from the reference value. Finally, the beginning and end of a ST episode are adjusted using a 0.05 mV threshold to locate the first and the last beats. The only particularity of our system is that two consecutive episodes must have at least 120 s to be considered as separate.

3. Results

In general, ischemia performance results are presented in terms of sensitivity (*Se*), expressing the detector sensitivity of ST-episodes identification, and positive predictivity (*PP*), giving the detector ability of true ischemic episode detection. These performance measures are defined as [12]:

$$Se = \frac{TP_S}{TP_S + FN}, \tag{3}$$

$$PP = \frac{TP_P}{TP_P + FP} \tag{4}$$

TP_S (True Positive) and *FN* (False Negative) are the number of matching and non-matching episodes respectively, when the reference annotations are the database annotations. Denominator of equation 3 gives the number of ischemic episodes. On the other hand, TP_P (True Positive) and *FP* (False Positive) are the number of matching and non-matching episodes respectively, when the reference annotations are the detector annotations. The denominator of equation 4 is the number of ischemic episodes annotated by the detector. The matching criteria of episodes found by the detector and the database annotations follow the protocol defined by Jager [12]: period of overlap between annotations includes either the extrema or at least 50% of the episode length.

Table 1 summarizes the results using two kinds of statistics: gross statistics, in which episodes of all patients are assigned equal weights, and average statistics, in which every patient is assigned equal weight. These statistics describe the performance of our system on the total database, since the total number of episodes is small.

	Gross Statistics		Average Statistics	
	Se (%)	*PP* (%)	*Se* (%)	*PP* (%)
Channel 1	72	67	73	81
Channel 2	68	60	73	84
Fusion	78	79	83	85

Table 1: Performance of our system in ischemia detection using gross and average statistics.

It can be observed that our fusion results are well balanced in terms of sensitivity and predictivity, for both gross and average statistics. Our best results in average statistics were then selected in order to compare to other system performances on the same database (see Table 2).

System	Average Statistics	
	Se (%)	PP (%)
Taddei [2]	84	81
Vila [4]	83	75
Jagger [3]	87	88
Maglaveras [5]	89	78
Andreão	83	85

Table 2: Comparative results of ischemic episode detection using average statistics.

4. Discussion and conclusions

We obtained one of the best average statistics in ischemic episode detection using a very simple approach. In particular, the positive predictivity of true episodes is only behind the one proposed by Jagger. Maglaveras reaches very good sensitivity to the detriment of a low positive predictivity.

We have chosen to follow the ischemic episode definitions to be consistent with the database annotations. This way, we use less rules then generally done by other articles [2,3,4,5].

One of the main advantages of our system is the fusion strategy, which combines complementary information of both channels. Furthermore, when the information is missing in one channel, a single-channel analysis is then carried out.

An original beat detection and segmentation approach using HMM was employed to extract the required information from ST-segment change analysis. Some authors [2,5,6] have affirmed that automatic segmentation of PQ segment and J point detection are always problematic. They have proposed instead to use a fixed position from the QRS fiducial point, which could be more robust to detection inaccuracies. Another alternative is to consider the whole ST-segment pattern [5, 6] rather than a reference point, as used here. These strategies will be studied in order to evaluate detection inaccuracies.

Non-ischemic episodes detection was not addressed in this work. In fact, ST-segment changes can occur for other reasons than ischemia [1]. Jager and Taddei dealt with this problem by searching for significant changes in electrical axis of the heart. Certainly, non-ischemic events must be studied more deeply to reduce false ischemia alarms.

Ambulatory ECG is commonly corrupted by noise. To carry out a robust analysis, it is preferable to reject noisy beats instead of treating them via noise reduction techniques. Therefore, some improvements in beat rejection can be achieved by adding other noise detection criteria, which considers the signal-to-noise ratio [3,6]. These issues will be the subject of our future works.

Acknowledgements

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